Human Liver Tissue Characterization Using Backscattered Ultrasound Signals Mean Scatterer Spacing

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Abstract—Using the backscattered ultrasound signals, we studied the periodicity of in vitro healthy and pathological liver tissue, we utilized the mean scatterer spacing (MSS) as a parameter of tissue characterization, estimated by: Spectral Auto-Correlation (SAC), Spectral Correlation of the autoregressive model (AR-SAC) and the Discrete Wavelet Technique (DWT), in comparison between this three method, the result of simulation confirm that DWT with Fourier Transform together (DWT with FT) can provide a very effective tool to extract the MSS from such structure and characterize the tissue.

Keywords—Periodicity; Liver tissue; Mean scatterer spacing; Backscattered Ultrasound Signals

I. INTRODUCTION

The arrangement in the soft organs such as the liver, kidneys and spleens is a systematic repetition of a basic structural unit (triads' porticos in the liver, the nephrons in the kidney, and spleen trabecular). It is shown that this structure present a pseudo-periodic centers dispersed, resulting in a consistent periodicity in the data of the backscattered signal [1].

The distance between any two consecutive scatterers consistent in the ultrasonic signal is called "Inter Scatterer Spacing -ISS-". The spatially ordered collection of all these individual ISS for a given ultrasonic signal is called the distribution of the ISS. The mean value of the distribution of the ISS is known "Mean Scatterer Spacing -MSS-" [2-4].

It is shown that the MSS can be used as a characteristic of tissues [4-7, 9-10]. The modification of the natural periodicity of liver tissue indicates pathologies thereof. However, there are important classes of pathologies where the periodicity is interrupted at the inner of a localized volume of a tissue. Among these classes there is the metastatic liver tumor, liver cirrhosis ...

II. THE SIMULATION MODEL OF TISSUE

The mathematical model y (t) representing the structure of tissues is given as follows:

\[ y(t) = \sum_{i=1}^{L} a_i \delta (t - \tau_{1i}) + \sum_{i=1}^{M} b_i \delta (t - \tau_{2i}) \]  

(1)

In this equation, the first summation represents the semi-regular structure with \( a_i \) being the amplitude of the \( i^{th} \) wave reflected by a reflector located at a temporal distance equal to \( \tau_{1i} \) and \( L \) being the number of reflectors. The second summation is the random structure, with \( b_i \) being the amplitude of the wave reflected by a diffuser located at a time distance equal to \( \tau_{2i} \) and \( M \) is the number of diffusers. Some suggestions were made on the model given by equation (1) as follows:
1) The amplitudes \( a_i \) and \( b_i \) are random variables uniformly distributed in the interval \([0, 1]\).
2) The time between two reflectors of the semi-regular structure \( \Delta \tau_{1i} = \tau_{1i} - \tau_{1i-1} \) follows a Gaussian distribution (equation 2) mean \( \mu \) and variance \( \sigma \).

\[ P(\Delta \tau_{1i}) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{(\Delta \tau_{1i} - \mu)^2}{2\sigma^2} \right) \]  

(2)

3) The time between two diffusers of the irregular structure \( \Delta \tau_{2i} = \tau_{2i} - \tau_{2i-1} \) follows a Rayleigh distribution given as follows:
Parameter \( \frac{\Delta \tau_{2i}}{m^2} \exp \left( -\frac{1}{2 \Delta \tau_{2i}^2} \right) \) \( u(t) \) (3)

with \( u(t) \) is the unit step, the mean and variance are respectively given by:

\[
\mu^2 = \frac{\pi}{2} m^2 \quad \text{and} \quad \sigma^2 = m^2 \left( 2 - \frac{\pi}{2} \right), \quad m \text{ being a constant.}
\]

Fig. 1 represents different simulation structures, namely semi-regular, and irregular composite of a semi-regular and irregular structure with parameter of simulation are given in table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Designation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSS, ( \mu )</td>
<td>Mean scatter spacing</td>
<td>2( \mu ) s</td>
</tr>
<tr>
<td>N</td>
<td>Number of samples</td>
<td>1024 points</td>
</tr>
<tr>
<td>( \mu_r )</td>
<td>the mean time spacing of the reflectors</td>
<td>2( \mu ) s</td>
</tr>
<tr>
<td>( \mu_d )</td>
<td>the mean time spacing of the diffusers</td>
<td>0.1( \mu ) s</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>standard variance of the temporal spacing</td>
<td>( \mu/100, \mu/50, \mu/10 )</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal to noise ratio</td>
<td>10dB</td>
</tr>
<tr>
<td>SNR, s</td>
<td>Signal to noise ratio of the composite structure</td>
<td>5dB</td>
</tr>
<tr>
<td>( a_i )</td>
<td>Amplitudes of reflectors</td>
<td>[0 : 1]</td>
</tr>
<tr>
<td>( b_i )</td>
<td>Amplitudes of diffusers</td>
<td>[0 : 1]</td>
</tr>
</tbody>
</table>

Based on the equation (1), we cite two major issues that we can to work, the degree of regularity of the semi-regular structure and the power of the irregular structure, in this work we are interested in the degree of regularity of the backscattered signal.

The degree of regularity of the semi-regular structure is measured by the variance \( \sigma \) of the time interval between two reflectors. We shall see that the regularity of the structure affects the efficiency of the studied methods.

Thus, for the structure is semi-regular, the \( \sigma \) variance must be very small compared with the mean \( \mu \) (mean spacing).

This factor (degree of regularity) plays a crucial role because the variation \( \sigma \) allows us to encompass the different real models.

III. DISCRETE WAVELET TRANSFORM FOR MSS ESTIMATION

The discrete wavelet transform (DWT) is based on the continuous version, unlike the latter, the DWT uses a scaling factor and a translation discretized. Called dyadic discrete wavelet transform any base wavelet working with a scale factor \( u = 2^i \). It is clear that the discrete wavelet transform is implemented in practice in any digital system (PC, DSP, MAP has \( \mu P \ldots \) ) [14].

The multi-resolution analysis is used to analyze a signal into different frequency bands, allowing a view of the finer to coarser.

The ultrasound signal is written as follows:

\[
y(n) = y_r(n) + y_d(n) + w(n), \quad \text{ne} [1, N]
\]

\( N \) is the length of \( y(n) \). The term \( w(n) \) represents white Gaussian noise. The terms \( y_r(n) \) and \( y_d(n) \) represent the regular structure and the irregular structure (diffusion) of the backscattered signal respectively.

Using the property of linearity of the discrete wavelet transform, the equation (4) is given by,

\[
W_{2j} y(n) = W_{2j} y_r(n) + W_{2j} y_d(n) + W_{2j} w(n),
\]

\( j = 1, 2, \ldots J \)

Where the terms \( W_{2j} y_r(n) \), \( W_{2j} y_d(n) \) and \( W_{2j} w(n) \) represent respectively the wavelet transform of \( y_r(n) \), \( y_d(n) \) and \( w(n) \) at the decomposition scale \( j \).

The problem of the signal information extraction is equivalent to the problem of extracting \( W_{2j} y_r(n) \) from the sequence \( W_{2j} y(n) \) in the presence of the component \( W_{2j} y_d(n) + W_{2j} w(n) \).

We can apply the denoising algorithm and signal reconstruction in the field of Mallat wavelet [15-16] for the signal \( y(n) \), even in the presence of measurement and speckle noise.

Fig. 1. Different structures of backscattered signal model: (a) semi-regular structure, (b) irregular structure and (c) composite structure.
The separation is performed in the wavelet scale space, exploiting the behavior of wavelet transform at different scales decomposition j.

Wavelets that are often used in processing of discrete one-dimensional signal are Daubechies wavelets. For fast wavelet transform (DWT), functions are defined by a set of indices which is designated as the "wavelet coefficients of the filters."[14].

Applying the decomposition of backscattered signal described above according to equation (1) by the wavelet transform.

For six scales j = 1, 2... 6, in left we show the approximation information (a1, a2, a3, a4, a5 and a6) and in right, detail information (d1, d2, d3, d4, d5 and d6). It is observed that the periodicity information becomes more and more obviously with increasing scales. This is because the regular structure y(n) is the dominant low frequency bands. Therefore, we are interested by the wavelet decomposition structures at high levels (low frequency) instead of directly measuring the MSS from the original signal.

We note that the frequency becomes clearer as the scale j increases, until level 6 and above, the information begins to lose from the highest levels.

![Wavelet Transform Graphs](image)

**Fig. 2. Frequency Spectrum of levels: (a) D5 (b) D6, (c) and A4 (d) A5.**

respectively, and it is easy to decide the MSS value especially for level A4, it proves to be sufficient to extract the MSS value from this level for accuracy and not to miss the exact value of MSS proposed testimony other levels A5, D5 and D6.

**IV. COMPARISON OF DISCRETE WAVELET TECHNIQUE AND OTHER METHODS FOR MSS ESTIMATION**

We present in this section a comparison of the methods SAC-AR [8] and the method using the discrete wavelet technique while maintaining the same parameters of a suitable human tissue, which are shown in Table 1.

The figure (Fig. 4) shows a comparison between the SAC-AR and TOD method, we studied the effect changing the value of the variance in the ultrasound simulated signal tell in Table 1 and calculate the value of MSS and study the influence on the results of applying these methods.

The results prove that the estimation of MSS by the discrete wavelet technique is better in all models (for to σ = μ / 100, σ = μ / 50, σ = μ / 30 and σ = μ / 10). The TOD can seem to be sensitive to the variation of σ. Table 2 shows the different values of the estimated MSS. The values estimated by the TOD method are close to the true value of MSS.

**TABLE II.** MSS COMPARISON OF SAC-AR AND DWT METHODS (*10^6).

<table>
<thead>
<tr>
<th>Method</th>
<th>σ=μ/100</th>
<th>σ=μ/50</th>
<th>σ=μ/30</th>
<th>σ=μ/10</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAC-AR</td>
<td>5.03</td>
<td>5.04</td>
<td>5.14</td>
<td>5.50</td>
</tr>
<tr>
<td></td>
<td>± 0.03</td>
<td>± 0.04</td>
<td>± 0.07</td>
<td>± 0.43</td>
</tr>
<tr>
<td>DWT</td>
<td>5.03</td>
<td>5.003</td>
<td>5.013</td>
<td>5.03</td>
</tr>
<tr>
<td></td>
<td>± 0.01</td>
<td>± 0.01</td>
<td>± 0.02</td>
<td>± 0.06</td>
</tr>
</tbody>
</table>

**V. CONCLUSION**

We conclude that the discrete wavelet transform can be effectively used to indicate the value of the mean scatterer spacing, it offers a finer level of signal analysis and to better adapt to local properties. Therefore it become an efficient tool
in signal processing for diseases detection from biomedical signals, as in this case, the calculation of MSS of a liver tissue being to distinguish between a healthy tissue or pathological. However, using the discrete wavelet technique with the Fourier transform together can provide a very effective tool to extract this parameter of such structure.

REFERENCES


Fig. 4. MSS (in Hz) estimated using ACF-AR, TOD to (a) σ = μ / 100 (b) σ = μ / 50, (c) σ = μ / 30 and (d) σ = μ / 10.